From Predicting Mosquito Habitat to Malaria Seasons Using Remotely Sensed Data: Practice, Problems and Perspectives

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Remote sensing techniques are becoming increasingly important for identifying mosquito habitats, investigating malaria epidemiology and assisting malaria control. Here, Simon Hay, Bob Snow and David Rogers review the development of these techniques, from aerial photographic identification of mosquito larval habitats on the local scale through to the space-based survey of malaria risk over continental areas using increasingly sophisticated airborne and satellite-sensor technology. They indicate that previous constraints to uptake are becoming less relevant and suggest how future delays in the use of remotely sensed data in malaria control might be avoided.

It has long been understood that mosquito numbers depend on climate[1] and that meteorological variables are of use in predicting the onset and severity of malaria epidemics[2]. Decades later, our understanding of how factors such as temperature, humidity and rainfall influence mosquito population dynamics has improved considerably[3], along with the sophistication with which weather variables can be used to predict malaria transmission rates[4]. Furthermore, many mosquito species, especially in temperate regions, oviposit in specific aquatic habitats that support characteristic plant communities and, hence, are easily identified[5]. Research that has used remote-sensing techniques to investigate mosquito and malaria ecology stems from the understanding that aerial and space-borne sensors could provide relevant surrogate information relating to the spatial variation in these meteorological and vegetation variables[6].

The advantages of remote sensing for epidemiological applications in terms of the rate, geographical extent and spatial and spectral resolution of data collection have been well documented[7,8]. However, the disadvantages regarding the interpretation and quality of such data are less widely appreciated[9]. Previous reviews of remote sensing applied to the problems of mosquito and malaria control[10,11], and to the study and control of a range of arthropod-borne diseases[12], have explored the relationships between remotely derived surrogates for the ecological determinants of disease vector distribution and abundance. The aim of this article is not simply to reiterate or update these works, but to outline the progression of research with respect to malaria epidemiology, so that an understanding can be gained of how remote-sensing techniques have been adopted. This background enables us to anticipate and plan for the opportunities made available by forthcoming advances in satellite-sensor technology[8].

It is necessary to outline several items of background information from the outset. The details of the spectral, spatial and temporal resolutions of the space-borne sensors mentioned in this review are provided in Table 1. The basic physical principles underlying remote sensing and some simple image classification techniques are outlined in Box 1. Box 2 summarizes the derivation of the normalized difference vegetation index (NDVI), a commonly used product of satellite-sensor data. Finally, Box 3 provides some important universal resource locators (URLs) for remote-sensing-related information on the Internet.

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Aerial survey and larval habitat mapping

In 1971, National Aeronautics and Space Administration (NASA) scientists first investigated the use of colour-infrared (CIR) aerial photography to identify the larval habitat of the nuisance saltmarsh mosquito *Aedes sollicitans*[13]. This species was known to oviposit in saltmarshes intermittently flooded by freshwater. Furthermore, 90% of such habitats were dominated by *Spartina patens* and *Juncus roemerianus* vegetation. The report documents that in this qualitative study, these vegetation assemblages were 'extremely accurately' identified by manual interpretation of the CIR aerial photographs at an 80 ha test site near New Orleans.

CIR aerial photography has also been used as a rapid method to map land-cover in a newly created mosquito control area[14]. In the Saginaw and Bay Counties of Michigan, in addition to nuisance floodwater *Aedes* mosquitoes, *Ae. triseriatus* (the vector for California encephalitis) and *Culex* spp (vectors for St Louis encephalitis) that breed in tree-hole pools were a significant public-health problem. Forested and open wetlands, marshes and residential areas were identified manually from the CIR aerial photographs and, in combination with the known flight range of each mosquito, were used to identify control priorities for the local population. The subsequent control scheme was of relatively low economic and environmental cost, as the area designated for insecticide treatment was considerably reduced, compared with the alternative of broadcast aerial spraying.

The purpose of these studies was to identify larval habitats of mosquito species that constituted a significant nuisance or public-health risk, so as to direct larval control more efficiently. Although simple and empirical, species–habitat correlations from CIR aerial photography have been, and continue to be, cited as more cost-effective than conventional ground survey techniques for obtaining information on the distribution of potential larval habitats; for example for *Psorphora columbiae* in both Louisiana[15] and Texas rice fields[16,17], and for *C. annulirostris* in urban areas of Queensland[18].

Table 1. The spectral, spatial and temporal resolution of the sensors carried by the SPOT, Landsat, IRS, NOAA and Meteosat satellites

	Resolution		
Satellite-sensor system	**Spectral[a]**	**Spatial[b]**	**Temporal**
Satellite Pour l'Observation de la Terre (SPOT)			
High Resolution Visible (HRV)	Ch 1 (0.51–0.73)	10 m	26 days[c]
Panchromatic mode (HRV-PAN)	Ch 2–4 (0.50–0.89)	20 m	
Multispectral mode (HRV-XS)			
Landsat-1, -2, -3			
Return Beam Vidicon (RBV) camera	Ch 1–3 (0.475–0.830)[d]	80 m	18 days
Landsat-1, -2, -3, -4, -5			
Multispectral Scanner (MSS)	Ch 4–7 (0.5–1.1)	79/82 m[e]	16/18 days
Landsat-4, -5			
Thematic Mapper (TM)	Ch 1–5 and 7 (0.45–2.35)	30 m	16 days
	Ch 6 (10.40–12.50)	120 m	
Indian Remote Sensing (IRS)			
Linear Imaging and Self Scanning (LISS)	Ch 1–4 (0.45–0.9)	36.5m	22 days
National Oceanic and Atmospheric Administration (NOAA)			
Advanced Very High Resolution Radiometer (AVHRR)	Ch 1–5 (0.58–11.50)	1.1 km	12 h
Meteosat-4, -5, -6			
High Resolution Radiometer (HRR)	Ch 1 (0.40–1.10)	2.5 km	0.5 h
	Ch 2–3 (5.70–12.50)	5 km	
Earth Observation Satellite (EOS)[f]			
MODerate Resolution Imaging Spectroradiometer (MODIS)	Ch 1–2 (0.620–0.876)	250 m	1–2 days
	Ch 3–7 (0.459–2.115)	500 m	
	Ch 8–36 (0.405–14.385)	1000 m	

[a] The spectral resolutions are the electromagnetic wavelength range in μm where 0.3 is at the visible and 14 the thermal infrared end of the spectrum.
[b] The spatial resolution is given as the diameter of the viewing area directly below the sensor; for the purposes of this review, high resolution sensors are arbitrarily defined as those with viewing areas less than 1000 m.
[c] A pointing facility can increase the frequency of coverage.
[d] Landsat-3 had a fourth RBV channel (0.505–0.750) at 30 m spatial resolution.
[e] The spatial resolution is 79 m for Landsat-1 to -3 and 82 m for Landsat-4 and -5, with the temporal resolution changing accordingly.
[f] EOS-AM is scheduled for launch in 1998.

Box 1. The Principles of Remote Sensing

Most sensors, from the human eye to satellite-borne multispectral scanners, measure radiation in various regions of the electromagnetic spectrum (EMS), emitted, reflected or scattered from natural objects. Because such objects reflect, absorb and emit radiation differently throughout the EMS, we can characterize them with a 'spectral fingerprint'. Passive optical remote sensing uses the sunlight reflected and re-radiated from the Earth. This radiation can be focused through a camera lens to expose film differentially sensitive to the EMS, or focused through telescopes and optical filters to detectors that respond to particular waveband ranges or channels. Active radar remote sensing is somewhat different in that a relatively long wavelength signal (3–30 cm) is generated by the orbiting platform and reflections of this signal by land surface features are detected by its sensors.

In all radiometers, the voltages recorded by detectors are turned into digital numbers, which are then calibrated to geophysically meaningful values using empirical relationships specific to each sensor. These numbers are then subjected to many stages of processing before distribution. The majority of remote-sensing research is concerned with understanding atmospheric and surface interactions that affect the precision of this satellite-sensor information and much of the rest with its validation through application to atmospheric, meteorological and ecological processes. A comprehensive introduction to the field of remote sensing is given in Ref. 51 and techniques that can be applied usefully by the epidemiologist are detailed in Ref. 9.

Remotely sensed images are usually represented as a two-dimensional array of squares (picture elements or pixels) on the computer screen. Pixel data can be related directly to features on the ground using a variety of correlation methods. Alternatively, the satellite sensor data can be clustered on the basis of the spectral similarity of pixels across an image, or within an area of interest. Results from such an unsupervised classification can then be used to guide fieldwork. Finally, when field information is available for part of an area, it may be used to train a supervised classification, which can then be used to predict the distribution of the resource (eg. land-cover type, mosquito breeding habitat) across the whole scene.

Box 2. Spectral Vegetation Indices

Spectral vegetation indices (SVIs) exploit the fact that healthy vegetation has a low reflectance in the visible red [eg. Advanced Very High Resolution Radiometer (AVHRR) channel 1] because photosynthetic pigments in plant tissues absorb such light and reflect strongly in the near-infrared (eg. AVHRR channel 2) as the structure of mesophyll tissue reflects radiation at these wavelengths[52]. This behaviour is rare in other natural objects, such as the soil background, so SVIs have been developed to enhance this contrast. The normalized difference vegetation index (NDVI) is the most commonly used SVI and is defined for the Landsat-Thematic Mapper (TM) as:

$$\mathrm{NDVI} = \frac{(\text{Channel 4} - \text{Channel 2})}{(\text{Channel 4} + \text{Channel 2})}$$

and for the National Oceanic and Atmospheric Administration (NOAA)-AVHRR as:

$$\mathrm{NDVI} = \frac{(\text{Channel 2} - \text{Channel 1})}{(\text{Channel 2} + \text{Channel 1})}$$

The result is a bounded ratio with possible values between -1 and $+1$. In practice, values are recorded well within these limits: 0.0–0.2 corresponds to bare ground, 0.2–0.7 indicates the presence of actively photosynthesizing vegetation, and negative values indicate water[53].

Box 3. Useful Universal Resource Locators (URLs)

The following list of URLs is not comprehensive. It provides the location of homepages for the current and future satellite systems mentioned in this article, pointers to image processing, geographical information system (GIS) and global position system (GPS) software, as well as information on epidemiologists conducting the types of research reviewed in this article.

Remote-sensing systems

SPOT-HRV	http://www.spotimage.fr/
Landsat-TM	http://geo.arc.nasa.gov/sge/landsat/landsat.html
NOAA-AVHRR	http://ns.noaa.gov/socc/socc-Home.html/
Meteosat-HRR	http://www.esrin.esa.it/esa/descrip/
EOS-MODIS	http://ltpwww.gsfc.nasa.gov/MODIS/MODIS.html
JERS-SAR	http://hdsn.eoc.nasda.go.jp/guide/homepage.html

Image-processing software

EASI/PACE	http://www.pci.on.ca/
ENVI	http://www.envi-sw.com/
ERDAS	http://www.erdas.com/
ER Mapper	http://www.ermapper.com/

GIS software and information

Arc-info	http://www.esri.com/
Idrisi	http://www.idrisi.clarku.edu/
Mapinfo	http://www.mapinfo.com/

GPS software and information

Garmin	http://www.garmin.com/
Magellan	http://www.magellan.com/
Trimble	http://www.trimble.com/

Research groups using remote sensing for vector-borne disease control

CHAART	http://geo.arc.nasa.gov/sge/health/chaart.html#mou
MALSAT	http://www.liv.ac.uk/lstm/malsat.html
MARA	http://www.malaria.org.za/
OTRG	http://users.ox.ac.uk/~zool0048/
TALA	http://users.ox.ac.uk/~zool0120/

Investigators were quick to exploit these early successes and move from aerial photography to aerial and space-based observations with multispectral scanners (MSSs). Improvements in *Spartina–Juncus* community discrimination for *Ae. sollicitans* control were soon demonstrated using an airborne MSS that could also collect data over much larger areas of the Mississippi delta[19]. Landsat-1 and -2 MSS data (see Table 1) were then used for the first time to identify freshwater plant communities associated with the larval habitats of *Ae. vexans* and *C. tarsalis* in riparian habitat bordering the Niobara river between South Dakota and Nebraska[20]. A supervised classification (see Box 1) using multiple-date Landsat-MSS scenes identified these aquatic habitats with 95% accuracy. This move from analogue photographic to digital multispectral scanning techniques was important because it facilitated the move to quantitative analyses which, in turn, enabled the investigation of more subtle variation in environmental variables and, thus, mosquito habitat suitability.

Aerial survey of habitat suitability

The first research component of NASA's Global Monitoring and Disease Prediction Program (GMDPP) investigated populations of *Anopheles freeborni* in the rice fields of California (see Fig. 1a and b) – an accessible model for the study of anopheline vectors in irrigated rice habitats[21]. Larval populations were sampled fortnightly throughout the period of rice development, while an airborne MSS simultaneously collected data with spectral and spatial resolutions designed to simulate that of the Landsat-Thematic Mapper (TM)[22] (see Table 1). An example of such imagery is shown in Fig. 1c. The data were first processed to provide an NDVI (see Box 2), and fields with higher NDVI values (correlated with high rice tiller densities) in the early growing season were found to have higher larval mosquito densities. Importantly, this distinction was possible two months before the peak in larval anopheline numbers. Furthermore, a linear discriminant analysis using the individual channel data was able to separate fields of high and low anopheline density to an overall accuracy of 75%. A repeat survey included data on the distance to livestock in a geographical information system (GIS)[23,24]. Incorporating this livestock information in a subsequent discriminant analysis enabled high and low larval density fields to be distinguished to an overall accuracy of 85%, indicating the importance of host availability in determining *An. freeborni* habitat suitability.

The increasing number of successful applications of remote-sensing techniques to mosquito habitat mapping, largely in the more accessible regions of North America, provided sufficient foundation to transfer these

Fig. 1. Irrigated rice fields in the lower Sacramento Valley of California seen from the ground (a), from the air (b), and from the Landsat-Thematic Mapper (c). Bands 5-4-3 are displayed as red, green and blue, respectively, so that in this image the rice fields appear dark green.

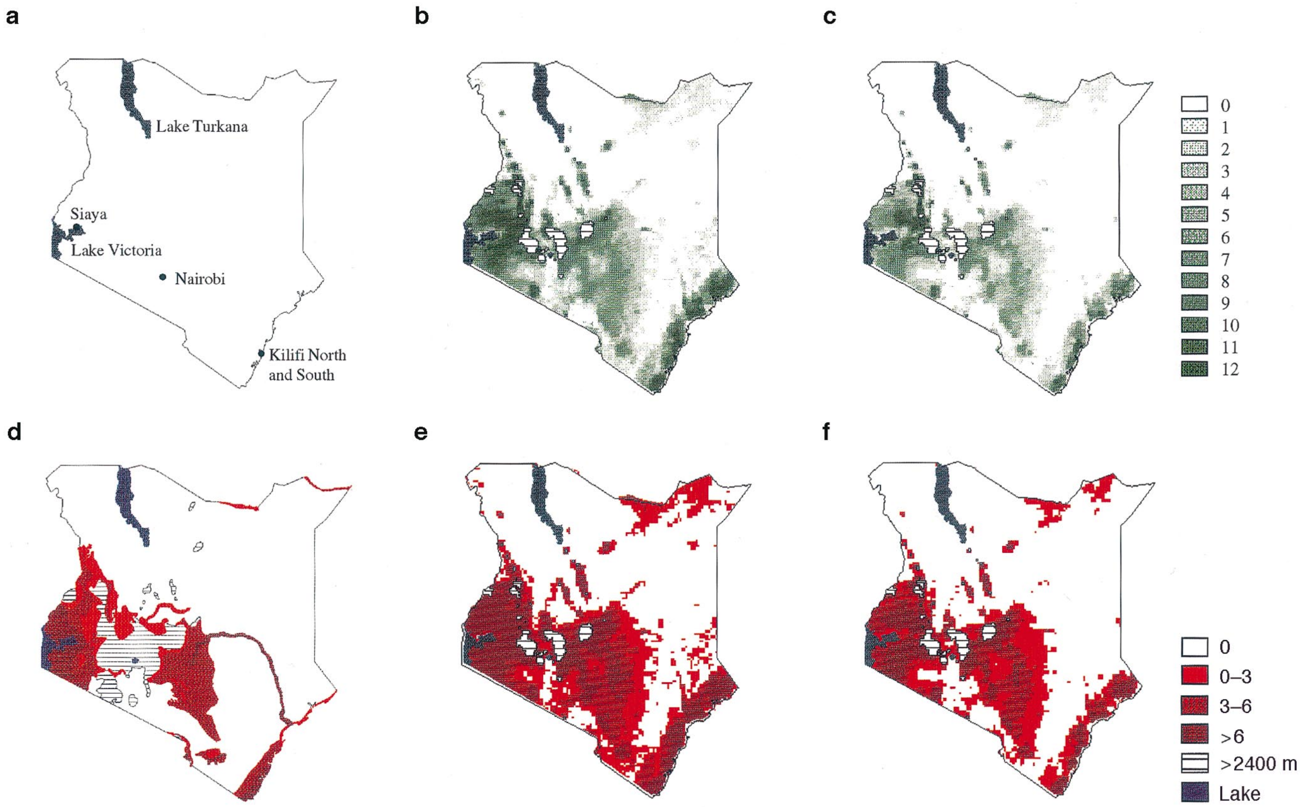

Fig. 2. Predictions of malaria seasonality in Kenya (a–f). The maps show (a) the location of the study sites and principal landmarks in Kenya; (b, c) the number of months for which malaria transmission is possible determined by the 0.35 and 0.40 normalized difference vegetation index (NDVI) threshold, respectively; (d) a reproduction of the Butler (1959) map of malaria transmission periods in Kenya; the hatched section of this map is defined simply as malaria free and does not relate to the hatched areas above 2400 m in the predicted maps; the white area is defined as malarious near water; (e, f) the number of months for which malaria transmission is possible determined by the 0.35 and 0.40 NDVI threshold, respectively, but recoded into the Butler (1959) categories for visual comparison with (d). The keys to the first and second rows of maps are provided on the far right of the figure. North is to the top of the page.

approaches to satellite-borne sensor mapping of remote tropical areas, where both logistical and public-health problems are significantly greater.

Space survey and habitat mapping

In this review, the ability to resolve areas smaller than 1×1 km is used as the criterion for defining high spatial resolution. Satellite sensors in low-altitude orbits can achieve high spatial resolutions at the cost of lower temporal resolution (ie. long periods between repeat measurements of a specific area of the Earth); in general, the converse is true of high-altitude satellite-sensors. The consequent merits and demerits of these systems for epidemiological research depends on many factors, which have been documented in Ref. 9.

High spatial resolution satellite sensors. The second research phase of the NASA-GMDPP project investigated the distribution of *An. albimanus* and *An. pseudopunctipennis* malaria vectors in the Chiapas region of Mexico[25]. Dry and wet season Landsat-TM scenes of the study area were subjected to an unsupervised classification (see Box 1), with areas of spectral homogeneity assigned to land-cover types using CIR aerial photographs and field inspection[26]. Field sites were sampled for mosquito larval density and botanical and hydrological variables; using a cluster analysis, the sites were grouped into 16 habitat types. The land-cover categories were then ranked as having high, medium or low 'mosquito production potential', based on correlations between these habitat types and land-cover. Only 9% of the designated control area was of high mosquito production land-cover types, allowing for considerable reductions in control effort and resources.

An independent study demonstrated how Landsat-TM data could be used to identify villages at high risk of malaria transmission within the Tapachula region of Chiapas, Mexico[27,28]. Again, dry and wet season scenes were subjected to an unsupervised classification and a stepwise discriminant analysis used to establish the relationship between vector abundance and land-cover. Land-cover in a 1 km buffer area surrounding the perimeter of the village was analyzed because this corresponded to the known flight range of *An. albimanus*. Transitional swamp and unmanaged pasture were found to be the most important land-covers for *An. albimanus*, and their combined area in the buffer zone was sufficient to predict high and low vector abundance in 40 villages to an overall accuracy of 90%. Furthermore, these relationships were sufficiently robust to predict the abundance of adult *An. albimanus* in a further 40 randomly selected villages from the neighbouring Huixtla region to an overall accuracy of 70%, using more multi-date Landsat-TM scenes[29].

Satellite Pour l'Observation de la Terre (SPOT) High Resolution Visible (HRV) data (see Table 1) have also been used successfully to predict adult *An. albimanus* densities in northern Belize[30] and to predict the distribution of *An. pseudopunctipennis* in central Belize[31]. Moreover, Indian Remote Sensing (IRS) satellite Linear Imaging and Self Scanning (LISS) II sensor data (see Table 1) have been used to identify 'mosquitogenic' conditions around Delhi and produce maps to inform local mosquito control activities[32].

Low spatial resolution satellite sensors. Multitemporal NDVI data (see Box 2) at 8×8 km spatial resolution from the National Oceanic and Atmospheric Administration's (NOAA) Advanced Very High Resolution Radiometer (AVHRR) have been applied to the problem of Rift Valley fever (RVF) epidemics in Africa[33,34]. The work showed that high NDVI values in Kenya were good indicators of seasonally flooded linear depressions, known as dambos. These habitats were highly suitable for *Aedes* spp mosquito breeding and, hence, closely associated with RVF epidemics. The work progressed to incorporate higher spatial resolution Landsat-TM and multispectral SPOT-HRV imagery to locate individual areas of high RVF risk determined by the NDVI[35]. However, operational application of the technique was hindered because investigators were not able to discriminate flooded from dry dambos in such images. Data from an airborne Synthetic Aperture Radar (SAR) were then incorporated to detect dambo flooding status[36]. A significant advantage of using SAR was that data collection was independent of cloud coverage, but the spatial resolution of satellite-borne SAR was not sufficient to reveal many of the smaller dambos in the region.

A recent alternative approach, however, has demonstrated that land-based radar may be capable of predicting habitat flooding status[37]. Radar was used in this study to estimate rainfall in Collier County, Florida. This information, in combination with data from tide-tables, was used to guide surveys for recently inundated saltmarsh habitats suitable for the oviposition of *Ae. taeniorhynchus* larvae. Rain, tides and rain-plus-tide events triggered 48, 26 and 26%, respectively, of proposed inspections, and this information system located seven of the eight broods of mosquitoes found during the study and control period.

NDVI data derived from the NOAA-AVHRR (see Box 2) have also been used in the Mar Chiquita lake region of central Argentina to predict the abundance of *Aedes albifasciatus*, an important livestock nuisance and vector of western equine encephalitis in the region[38]. The authors argue that such relationships could be used to monitor and predict future surges in the population of this particular floodwater mosquito.

Remote prediction of disease-risk distribution

The majority of the above applications focus upon remote identification of mosquito habitats, and the prediction of mosquito numbers. Recent investigations have tried to relate this to the transmission of *Plasmodium falciparum* by anophelene vectors in Africa.

In studies of the potential of NOAA-AVHRR and Meteosat-High Resolution Radiometer (HRR) data to predict malaria risk in The Gambia[39,40], although clear relationships were demonstrated between satellite-sensor data and meteorological variables associated with malaria transmission, owing to the complexity of the inter-relationships, it was difficult to predict how these would affect adult mosquito abundance. Furthermore, the relationships between malaria incidence and environmental variables were complicated by sociological factors: in areas where anopheline abundance was greatest, and hence biting most frequent, people were more likely to protect themselves with insecticide-impregnated bednets.

Despite these complications, predictions of malaria seasonality (the combination of disease risk in space and time) in Kenya have been achieved by establishing relationships between childhood malaria cases (with disease data collected during on-going surveillance of severe malaria morbidity in five communities in Africa)[41] and contemporary imagery from the NOAA-AVHRR and Meteosat-HRR[42]. The remotely sensed data were first processed to provide surrogate information on land surface temperature (LST), rainfall [expressed as cold cloud duration (CCD) or the number of hours for which a given pixel was covered by cloud below a threshold determined as rain bearing], reflectance in the middle infrared (MIR) wavelengths and the NDVI. These variables were then subjected to temporal Fourier processing[43] and compared with the mean percentage of total annual malaria admissions recorded each month at three sites in Kenya. The NDVI lagged by one month was found to be the most significant and consistently correlated variable with malaria admissions across the sites

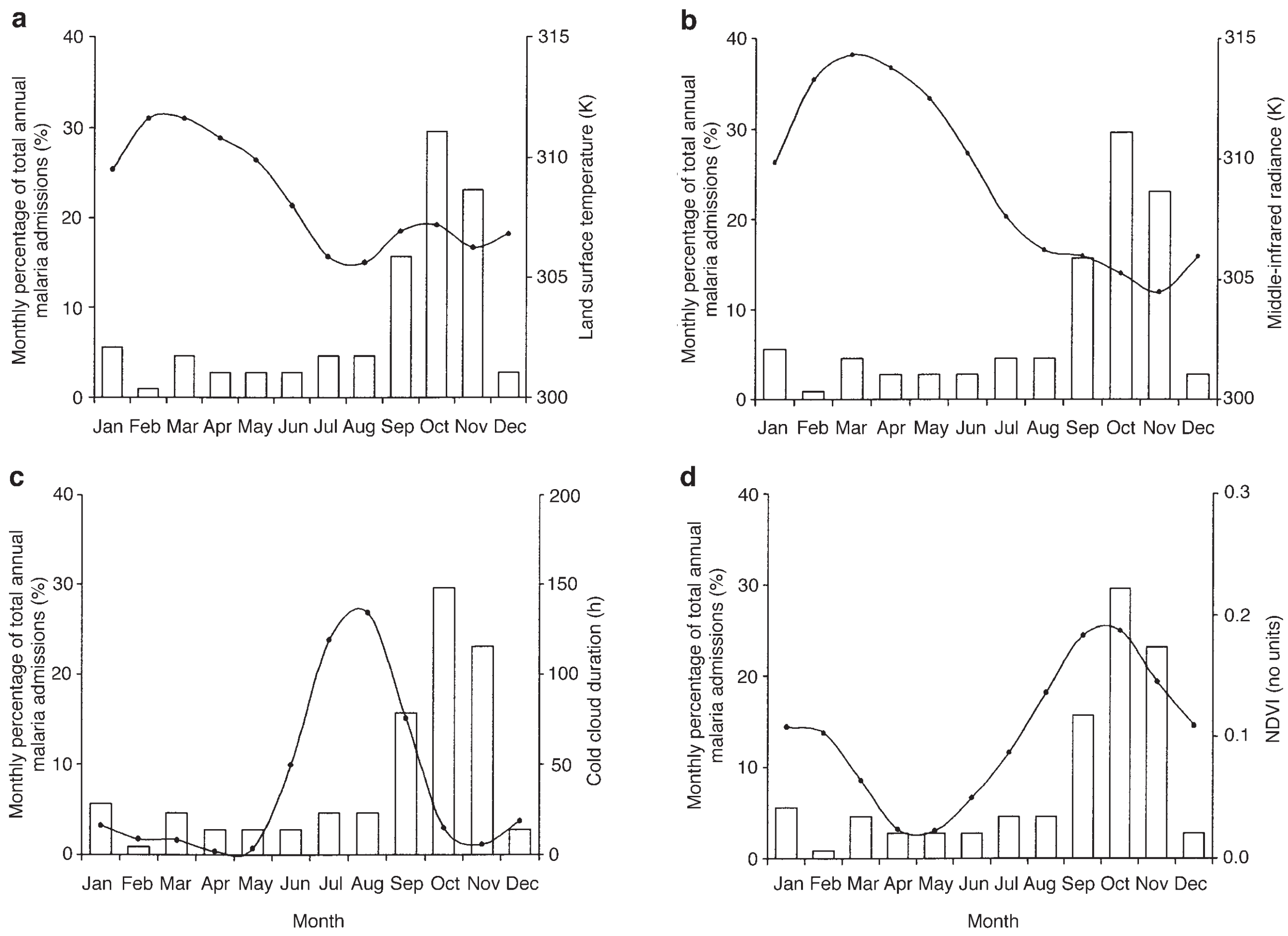

Fig. 3. Graphs (a–d) show the time-series of monthly temporal Fourier-processed satellite-sensor derived variables (line) and the monthly mean percentage of total annual malaria admissions (bars) for Sukuta on the Atlantic coast of The Gambia. The results of linear regressions of malaria cases and satellite-derived variables is for land surface temperature (a) (adjusted $r^2 = -0.41$, NS; d.o.f. = 10); for middle-infrared radiance (b) [adjusted $r^2 = -0.62$ ($P \ll 0.01$; d.o.f. = 10)]; for cold cloud duration (c) lagged by two months [adjusted $r^2 = 0.86$ ($P \ll 0.01$; d.o.f. = 10)] and for the normalized difference vegetation index (d) lagged by one month [adjusted $r^2 = 0.66$ ($P \ll 0.01$; d.o.f. = 10)]. d.o.f., degrees of freedom; NS, not significant.

(mean adjusted $r^2 = 0.71$; range, 0.61–0.79). Subsequent regression analyses showed that an NDVI threshold of 0.35–0.40 is required for more than 5% of the annual malaria cases to be presented in a given month. Spatial extrapolation of these thresholds allowed the number of months for which malaria admissions could be expected to be defined across Kenya. The resulting 'malaria season' predictions were compared with a map of malaria transmission periods compiled from expert opinion[44] and are shown for comparison in Fig. 2. The correspondence is remarkable when the deficiencies inherent in compiling the original map are acknowledged. The authors stress that the maps produced did not constitute a definitive picture of malaria transmission in Kenya but were a demonstration of methodology. It was considered that much more validation of the relationship between malaria admissions and NDVI was required to check its robustness in space and time.

The mapping of malaria seasonality is an important goal because, despite *Plasmodium falciparum* being arguably the most important pathogen to which children in sub-Saharan Africa are exposed[41], many national malaria control programmes lack detailed disease-risk maps to guide intervention. In resource-constrained environments, such maps could: (1) optimize the timing of insecticide distribution for impregnating bednets, (2) restrict distribution of antimalarial drugs to periods of known disease risk to prolong their useful life-span, and (3) reduce the time required to provide logistically and financially demanding chemoprophylaxis.

Analyses similar to those performed in Kenya are shown here for Sukuta on the Atlantic coast of The Gambia. The correspondence between the remotely sensed LST, MIR, CCD and NDVI variables and malaria admissions is illustrated in Fig. 3. The environmental variables are of different relative importance in The Gambia and in Kenya. In both cases, LST and MIR have a negative relationship with malaria admissions, because rainfall not only creates potential breeding habitats, but also increases evapotranspiration and vegetation coverage, which cool the environment. In The Gambia, the NDVI lagged by one month has a strong association with malaria admissions, but with a significantly lower dynamic range (ie. annual variation between 0.0–0.2) and, thus, lower thresholds that support malaria transmission than in the three Kenyan sites. Furthermore, the strongly unimodal pattern of rainfall on the Gambian coast makes

CCD lagged by two months the best predictor of malaria admissions.

That the suite of ecological factors that influence malaria transmission vary across continental areas and through time is not surprising. The number and interaction of dependent factors result in a formidable complexity. The immediate response of researchers will be to move to area-specific monitoring of disease risk with the need to validate predictions over wider areas at increasingly higher spatial resolutions. Despite the desirability of these predictions to direct malaria control[45], the relevant epidemiological data to test predictions are often inadequate and initial maps should therefore be used with care. Considerably more research needs to be conducted to define the empirical relationships between vector contact, disease risk and remotely sensed variables. A more heuristic approach is to model population dynamics in real-time using remotely sensed correlates of life-history parameters, a methodology already successfully demonstrated with ground-measured climate data and population modelling of tsetse[46], *Glossina* spp, and the tick *Rhipicephalus appendiculatus* across Africa[47]. Such studies are possible retrospectively with current satellite-sensor systems, where existing vector population records are available, but will become increasingly feasible with data from the next generation of satellite sensors.

Future satellite sensors

Many new satellite-sensor systems are scheduled for launch to coincide with the millennium[8] and, while most represent simple refinements of existing satellite-sensor series, one has been designed with the specific objective of providing a regular global dataset of well-calibrated land surface data of high radiometric resolution. These data will be generated by the MODerate Resolution Imaging Spectroradiometer (MODIS) on-board the NASA Earth Observing System (EOS)-AM satellite to be launched in June 1998 (Ref. 48) (see Table 1). Improvements for the epidemiologist will be threefold. First the range of data available will increase substantially, with 36 channels from which to derive meteorological and other ecological variables. Moreover, these data will have significantly higher signal-to-noise ratios, as the channels have been designed with small waveband ranges to exploit 'spectral windows', where atmospheric signal attenuation is minimal. Second, MODIS will have a high temporal resolution (two-day repeat time) at significantly higher spatial resolution (250×250 to 1000×1000 m, depending on the channel) than existing sensors, in effect resulting in hybrid data with characteristics of both the NOAA-AVHRR and Landsat-TM. Third, the stated aim is to ingest, process and disseminate data within three days of acquisition, including many potentially useful products, such as improved spectral vegetation indices, land surface temperature and evapotranspiration estimates, although this service is likely to become operational some time after the launch of MODIS. This means that much of the routine data processing will be performed at source, giving unparalleled rapid access to contemporary data on large-area ecosystem processes. In anticipation of these advances, it is prudent for epidemiologists to start collecting geo-referenced field data as a routine addition to existing projects. This can be achieved cheaply and efficiently with current hand-held global position systems (GPSs), although differential GPS will be required for high spatial resolution studies (see Box 3).

Conclusion

Mosquito and malaria control are problems that can be perceived at many spatial scales, ranging from the catchment areas of rural health clinics concerned with individual patients to the regional and continental interests of international donor agencies concerned with the continental distribution of the disease and quantification of total malaria incidence. The variety of remote-sensing platforms and sensors provide data relevant to each of these spatial scales. Indeed, using a wide range of remotely sensed imagery to help understand the distribution of mosquitoes and mosquito-borne diseases, research has progressed significantly from habitat characterizations at high spatial resolution, to work that has inferred habitat suitability for both larval and adult mosquitoes and, further, from local- to regional-scale predictions of malaria seasonality.

From the initial studies in the late 1970s and early 1980s, it has taken a decade for this approach to become widely adopted and the use of remotely sensed imagery is still far from routine. Delays in uptake have been attributed to the perceived costs of image-processing equipment and expertise, lack of access to imagery and the novelty of the techniques. These factors need no longer be viewed as substantial constraints. Very sophisticated analyses can now be performed on relatively modestly priced computer systems. Furthermore, image-processing and GIS software are available that automate many image-processing tasks (see Box 3). Finally, and perhaps most importantly, satellite-sensor data have become more widely and freely available[49], especially to research workers in developing countries where the malaria challenge is the greatest.

In this review, we have shown that remote-sensing techniques can provide information important in predicting the spatial and temporal distribution of malaria, thereby enabling existing resources for research and control to be better directed. International agencies in cooperation with developing countries are now able to develop programmes to validate real-time predictions of malaria incidence and prevalence across continental areas. Research relating remotely sensed variables to mosquito life-history parameters is an essential basis for future 'disease forecasting' for a malaria early warning system (MEWS). This could operate in much the same way that drought and famine conditions are now routinely monitored using satellite-sensor data[50].

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